AUTONOMOUS AGRICULTURAL EQUIPMENT EVALUATION FOR BROAD-ACRE CROP PRODUCTION

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Research

HIGHLIGHTS

- Autonomous equipment was used for 127 seeding, spreading, and spraying operations.
- For seeding, autonomous operation was more efficient than conventional operation.
- For spraying and spreading, autonomous operation had similar efficiency to conventional operation.
- Introduced route efficiency metric.

ABSTRACT. *Automated technology helps an operator on a continuum from manual to fully autonomous. In order for autonomous systems to be a rational investment and economically feasible for a producer, autonomous equipment must have greater productivity or efficiency compared to equivalent human/conventional labor. In the agriculture industry, there has been an increase in labor costs and a shortage of skilled labor, which is a real threat to revenue from farming activities. Autonomous equipment may help alleviate and fill the gap of labor. An autonomous vehicle, the OMNiPOWER (Raven Industries, Sioux Falls, SD), was used for 127 seeding, spraying, and spreading operations (> 5700 ha) over a three-year period. Conventional equipment was used for 25 operations. Equipment and geospatial measures were recorded via Controller Area Network logs. Field efficiency, route efficiency, and fuel efficiency were calculated for operations. These results were compared with both manual conventional equipment performance and scientific literature values. For seeding, OMNiPOWER outperformed conventional equipment in terms of efficiency and fuel usage. For spraying and spreading tasks, OMNiPOWER performed on par with conventional equipment measured performance and literature review findings. Two case studies were performed using both conventional and OMNiPOWER equipment on the same field, one spraying operation and one spreading operation.*

Keywords. *Autonomous operation, Autonomy, Field efficiency, Fuel efficiency, Route efficiency, Seeding equipment, Spraying equipment, Spreading equipment.*

Modern agriculture faces large-scale challenges that were not as impending in the previous decades and centuries—worldwide climate change and rapid population growth. With malnutrition already a massive global issue, climate change will continue to put additional stress on agricultural production around the world (WHO, 2020). Precision Agriculture (PA)—an emerging term encountered across farming sectors worldwide—is the practice of using technological and equipment advancements to farm more efficiently, namely, to precisely apply farm inputs where, when, and with the correct quantity needed (Balafoutis et al., 2017). The objective of PA is to make more informed decisions with respect to best management practices (BMPs) such as the 4R's nutrient management principle (right source, right rate, right time, right place) while increasing productivity and reducing unnecessary inputs, waste, and environmental impacts (Pierce and Nowak, 1999; Fertilizer Canada, 2020). Of all the possible climate change adaptation and mitigation strategies available, technological developments in PA equipment are leading the latest wave of advancement. The adoption of technological/digital innovation in the agriculture sector has been deemed one of the most important changes which would help to eradicate hunger and poverty, as well as mitigate climate change impacts (United Nations, 2019). Improvements to modern agricultural processes have the potential to reduce excessive consumption of resources (fuel, water, external inputs), reduce physical environmental damage to soils (compaction), and minimize the release of contaminants to the environment (Maurel and Huyghe, 2017). Increased efficiency during agricultural operations will subsequently improve economic performance, saving time and financial resources for farmers (Maurel and Huyghe, 2017).

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Automation has long been incorporated into agriculture, and machine autonomy is a key driver of PA (Han et al., 2015). Automated technology helps an operator on a continuum from manual to fully autonomous (Parasuraman et al., 2000). In agriculture, there is currently no large-scale commercial use of agricultural robots (Abbasi et al., 2022). Historically, aspects of autonomy have been progressively added to agricultural machinery (Daum, 2021), and retrofitting autonomous technology has been shown to be technically and economically feasible (Lowenberg-DeBoer et al., 2021). For example, there has been success retrofitting conventional tractors (e.g., OmniDrive, Raven Industries; X-Pert, Precision Makers, and Autonomous Solutions) (Shockley et al., 2022). Due to the trend of research and innovations in this area, it is predicted that autonomous systems without the use of an operator in the cab will soon become commercially available (Edet and Mann, 2020).

In order for autonomous systems to be a rational investment and economically feasible for a producer, autonomous equipment must have a greater productivity or efficiency compared to equivalent human/conventional labor (Goense, 2003). In the agriculture industry there has been an increase in labor costs (Charlton and Castillo, 2021; Kalyanaraman et al., 2022) and a shortage of skilled labor (Ghobadpour et al., 2022; Kalyanaraman et al., 2022). In the context of Canadian agriculture, labor shortage is a very real threat to revenue from farming activities (26,400 unfilled jobs in 2014, equivalent to CAD $1.5B in losses), and shortages doubled between the years 2006–16, with a similar doubling in shortages expected between 2016–26 (CAHRC, 2016a,b). In addition to labor shortages, the average operator age of American (Zulauf, 2020) and Canadian farmers (Statistics Canada, 2022) has drastically increased in the last 40–80 years. The average farm size has increased significantly in the last forty years (Beaulieu, 2014; Key, 2019; Statistics Canada, 2016). Autonomous equipment may help alleviate and fill the gap of labor (Ghobadpour et al., 2022); using autonomous machines reduces operator overwork and exhaustion, helps save resources and time, and provides accurate data for refining the technology. Autonomous farm equipment is not yet widely used at the commercial farming scale; currently, it remains largely at the research level or on smaller scale operations due to high costs of sensors, maintenance, and lack of farmer trust (Beaujot, 2017; Petersen et al., 2017; Shamshiri et al., 2018). OMNiPOWER (formerly DOT, Raven Industries) is a U-shaped diesel-powered modular platform on which seeding, spraying, and spreading implements are attached as per operation (Cloete, 2019). A small to medium enterprise or farm comfortable with using autonomous equipment and experiencing a labor shortage can be a potential user of autonomy (Beaujot, 2017).

We hypothesized that autonomous operation would not be less efficient than manual, conventional operation. The methodology approach to test this hypothesis used an autonomous vehicle, the OMNiPOWER Platform (OP), for broadacre crop production and then compared results with both manual conventional equipment performance and scientific literature values.

Materials and Methods

In Field Operations

During the 2021, 2022, and 2023 seasons, partner producers were involved, and operations were accomplished at their farms in addition to operations at the Olds College Smart Farm (OCSF), all located in south/central Alberta (table 1). Data collection for conventional operations was only conducted in 2022 and was not possible for the other years of the study due to a lack of opportunity for collaboration with partner producers and a lack of resources (table 1). Equipment specifications (operating width, capacity, etc.) for both the autonomous and conventional equipment used are described in table 2. In order to conduct fair and reliable comparisons between the autonomous and conventional machinery, the types of crops produced were limited to small grains (canola, wheat, barley) that had similar seeding processes, as well as sowing in the same geographic region. The details of all field operations (inputs, crop types, location, equipment specification, etc.) are detailed in the Supplemental Material. Conventional operations were routed by the operator; however, typical state-of-the-art features were utilized during operations, including auto-steer navigation for straight AB lines, while turns were conducted manually.

To ensure consistency of data observations between all members of the research team, a common spreadsheet was developed in 2020 for an observer to manually record data during autonomous operations in a consistent format, then an improved version of the 2020 spreadsheet was used throughout the 2021, 2022, and 2023 seasons. These observations recorded fuel and product usage, in-field time, field size, crop type, weather conditions, issues, error codes, and

Table 1. Summary table of number of autonomous and conventional operations and total area covered while collecting data.

Year	Operation	Autonomous (OP)	Conventional
2021	Seeding	4 (34.3 ha)	N/A
	Spraying	19 (798.6 ha)	N/A
	Spreading	10 (539.8 ha)	N/A
2022	Seeding	7 (257.7 ha)	7 (295.0 ha)
	Spraying	13 (823.6 ha)	2 (124.8 ha)
	Spreading	41 (1733.7 ha)	16 (1990.1 ha)
2023	Seeding	13 (168.1 ha)	N/A
	Spraying	3 (122.3 ha)	N/A
	Spreading	17 (1242.5 ha)	N/A
Totals		127 (5720.6 ha)	25 (2409.9 ha)

Table 2. Comparison table of OP sizes (width, tank volume, and total maximum allowable weight when loaded with product, and engine power) compared to conventional equipment (includes combined tractor and implement loaded with product weight) used in 2022.

Operation	System	Implement Width (m)	Tank Size (L)	Total Weight (kg)	Engine Power (kW)
Seeder	Autonomous	9.144	12,366	23,605	129[a]
	Conventional	21.3	21,095	61,079	402.5
Sprayer	Autonomous	37.06	6,057	19,019	129[a]
	Conventional	36.5	4,542	18,615	242
Spreader	Autonomous	27.43	8,130	19,042	129[a]
	Conventional	25	5,663	N/A	253.5

[a] OP platform engine power is 129 (kW), regardless of the implement attached.

time spent on various activities. This style of category-based time tracking was used to support a more detailed data analysis using digital data. Since only observational data was available in 2020, all forthcoming results in 2020 are crude estimates of efficiencies since some parameters were estimated (fuel usage tracked during refueling only) or calculated using literature values (using published rates and/or average speeds of spraying/seeding equipment), unlike for 2021, 2022, and 2023, where all data shown in this report were digitally acquired.

Digital Data Acquisition & Analysis

Beginning during the 2021 growing season, a Somat eDAQ legacy unit (Model # 1-ECPU-PLUS-COM-2 base unit with 1-EHLS-B-2 Analog module) was added to the project to gather highly detailed digital data during autonomous operations. The Somat eDAQ provided accurate, consistent, and reliable synchronous data. The Somat eDAQ system was designed for working in harsh conditions, developed for mobile on- and off-road conditions as well as rugged and tough testing conditions. Modern agricultural equipment has adopted the J1939 protocol, a Controller Area Network (CAN) bus vehicle network communication standard developed specifically for agricultural and forestry heavy equipment (Stone et al., 1999). The CAN bus network allows reliable digital data to be shared between vehicle components such as the engine, transmission, dashboards, keypads, and operator controls. Information such as instantaneous fuel usage rates and engine speed is readily accessible through the network. CAN bus data accessed by the Somat eDAQ was effectively utilized during operations for calculations to determine equipment performance.

For the 2022 and 2023 growing seasons, the data acquisition equipment was upgraded with two new Somat eDAQXR units (Model #1-EDAQXRL-64GB-2 base with ELDIO.02 Digital I/O and ELHS.05 Analog modules, Hottinger Bruel & Kjaer, Marlborough, MA, USA), one to use with OP replacing the legacy Somat eDAQ unit utilized in 2021 and the other for the use of monitoring conventional equipment. The Somat eDAQXR used for monitoring conventional equipment was set up to be easily transferable between equipment based on the operational task at hand. The following pieces of equipment were used in 2022 along with the second Somat eDAQXR to capture conventional equipment data: 2020 Case IH Steiger 420 with 2019 18.3 m Seed Master Ultra SR, John Deere 4940 with New Leader L3030G4, 2017 New Holland T9.600 with New Holland P4580 Tow-Between Air Cart, New Holland 21.3 m P2060 Air Drill.

The Somat eDAQXR system was programmed to measure and record data at a rate of 2 Hz for a multitude of variables, including parameters that were gathered as helper variables or by default settings on the Somat eDAQXR. The data collected via Somat eDAQXR was the same for both the autonomous and conventional machinery. The following variables (a select few of the total) were utilized for analysis in this project:

- **Geographical data**: timestamp, altitude, latitude, longitude, number of satellites, heading, temperature.
- **CAN data**: electrical potential, engine coolant temperature, engine fuel rate, engine percent load at current speed, engine speed, total engine hours, OP battery voltage.
- **Somat data**: Somat auxiliary battery supply voltage.
- **Processed data**: Fuel used and total distance traveled since data recording commencement.

The data obtained from the Somat eDAQXR were used to create maps, graphs, and calculations. Maps were used to check areas of downtime/breakdowns of equipment, as well as to observe operational pathways and speeds of the equipment. The main outcome for each field operation dataset was to calculate route efficiency, field efficiency (via theoretical and effective field capacity), and fuel efficiency. There was high confidence in using the Somat eDAQXR for tracking fuel usage during this project, as based on prior research, CAN bus data had low error (±1 to 5%) of fuel consumption rates as compared to physically measured fuel rates, deeming it appropriate for management and research purposes (Marx, 2015).

Metric Calculations

Route efficiency is a parameter that quantifies the environmental footprint (soil compaction, potential crop damage, excess fuel use, etc.) during an operation. This parameter was not found in the literature, so it was developed during the course of this project as a way to account for overlap, turning, excessive driving, and other spatial obstacles leading to reduced route efficiency and driving/operational pathways. It is the relationship of the area meant to be covered (obtained from a rendered as-applied map after operations are finished) and the actual area covered (calculated from the total distance traveled and operational implement width). The equation used to calculate route efficiency is as shown in equation 1. A visual example of how route efficiency was calculated is shown in figure 1.

$$\begin{aligned} &\textit{Route Efficiency}\,(\%) = \\ &\Big\{\Big[\textit{As Applied Area}\,(ha) \times \left(10{,}000\ \mathrm{m}^2/\mathrm{ha}\right)\Big] \\ &\div \Big[\textit{Total Distance Traveled}\,(m) \\ &\times \textit{Width of Implement}\,(m)\Big]\Big\} \times 100 \end{aligned} \tag{1}$$

Field efficiency (eq. 2) is a common metric used for assessing the performance of agricultural equipment; it describes the extent to which a piece of equipment can perform its primary task. As defined by the ASABE standards, field efficiency ([E_f] is "the ratio of effective field capacity to theoretical field capacity, expressed as a decimal value" (ASABE Standards, 2020c). In this research, field efficiency was calculated as defined in the S495 standard and expressed as a percentage; the ratio of a machine's effective field capacity (EFC, eq. 3)—the actual rate of crop area processed in a given time (ASABE Standards, 2020c), to the machine's theoretical field capacity (TFC, eq. 4)—the rate of performance obtained if a machine performs its function 100% of the time at a given operating speed using 100% of its theoretical width (ASABE Standards, 2020c). Several factors

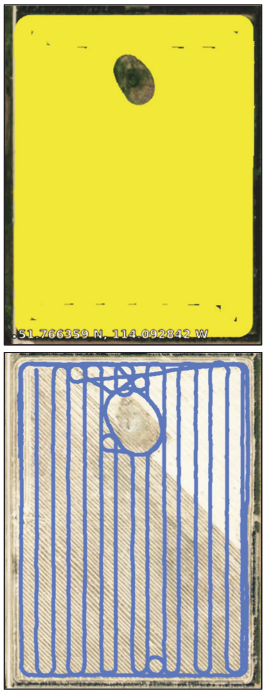

Figure 1. Top panel shows the as-applied map produced for the operator upon completion of an autonomous spraying operation; the shaded area represents the total applied area of 41.7 ha. Bottom panel shows lines depicting the path traveled by OP during the spraying operation. The actual area covered, calculated using the distance pathway multiplied by the operational implement width was 53.8 ha.

that can significantly negatively impact field efficiency are turning, idling, filling, maintenance, and field/implement shape and size. Calculations of field efficiency were based on the ASABE standards and results from various literature sources (ASABE Standards, 2020c; White, 1978; Hancock, 1991). By utilizing the Somat eDAQXR, machine ground speed was available; thus, EFC was calculated as a job-level measurement accumulated from all points in time. Unlike the aforementioned route efficiency calculation, which only considered spatial distance, field efficiency must also account for time spent during the operation in addition to the area covered. It is a measure of overall efficiency and can be applied to determine costs of labor, operating costs, and for the scheduling of tasks (Hanna and Hanna, 2016). As defined by the ASABE standards, "field efficiency accounts for the failure to utilize the theoretical operating width of the machine; time lost because of operator capability; habits and operating policy; and field characteristics ... The following activities account for the majority of time lost in the field: turning and idle travel; materials handling (seed, fertilizer, chemicals, water, harvested material); cleaning clogged equipment; machine adjustment; lubrication; and refueling" (ASABE Standards, 2020b). Total 'in-field' time was recorded for all operations; all types of idle time as described in ASABE Standard EP496.3 (2020b) were captured using the Somat eDAQXR for the purpose of calculating EFC and field efficiency of the machine operation.

$$Field\ Efficiency\ (\%) = \frac{EFC\ (ha\ /\ hour)}{TFC\ (ha\ /\ hour)} \times 100\% \tag{2}$$

where

$$EFC\ (ha\ /\ hour) = \frac{Actual\ Area\ Covered\ (ha)}{Total\ Field\ Time\ (hours)} \tag{3}$$

$$TFC\ (ha\ /\ hour) = \frac{Speed\ (km\ /\ h) \times Implement\ Width\ (m)}{10\ \text{km} \times \text{m}\ /\ ha} \tag{4}$$

Lastly, fuel efficiency was calculated as the total fuel used per hectare (L/ha). These three parameters were calculated for all field operations for which Somat data was collected throughout 2021, 2022, and 2023 on both autonomous and conventional operations.

Raw digital data obtained from the Somat eDAQXR required significant cleaning and manipulation prior to usability, and inferences could be made. Subsequently, data was processed, visualized, and analyzed using several programs: InField (Version 2.5.1), Python 3, ArcGIS Pro (Version 2.7.1), and RStudio (Version 1.4.1717). The majority of data and results are presented as preliminary observational summaries, due to low and/or uneven sample sizes, with the exception of seeding operations in 2022. Formal statistical analyses (parametric mean comparison; two-way t-test) were conducted to determine if there were any significant differences in field, route, and fuel efficiencies between conventional and autonomous seeding operations in 2022 and 2023.

Results and Discussion

Results

A general summary of the route, field, and fuel efficiencies for the past four years of the project are summarized in table 3. It can be noted that the efficiencies of OP have generally improved over the course of the project.

OMNiPOWER Performance 2020–23

With each additional year of working with the OP platform, many learnings, upgrades, and refinements made by Raven Industries and improved OP operator skills reflect the steady improvements seen in efficiencies. Average field efficiency for seeding increased from approximately 40% in

Table 3. Average efficiency parameters measured for autonomous operations during 2020–23 field seasons.

OP Summary		Route Efficiency	Field Efficiency	Fuel Efficiency L/ha
Operation	Year	(%)	(%)	(US gal/ac)
Seeding	2020	N/A	38.87[a]	N/A
	2021	66.25	50.92	8.69 (0.93)
	2022	83.78	74.17	5.28 (0.56)
	2023	69.36	52.52	8.97 (0.96)
Spraying	2020	N/A	45.65[a]	N/A
	2021	71.96	56.68	0.89 (0.09)
	2022	68.7	65.65	0.85 (0.09)
	2023	75.75	56.80	0.77 (0.08)
Spreading	2020	N/A	N/A	N/A
	2021	68.47	53.66	1.36 (0.14)
	2022	67.05	55.0	2.54 (0.27)
	2023	78.66	60.60	1.44 (0.15)

[a] Data captured with manual observations as digital data capture was not collected in 2020.

2020 to a high of 74% in 2022, then down to 52% in 2023 (fig. 2a), while route efficiencies display a similar trend, peaking in 2022 (~85%) (fig. 2b). Similarly, spraying field efficiencies improved from 46% in 2020 to 66% in 2022 and then declined to 57% in 2023 for spraying operations. Spraying route efficiencies, on the other hand, peaked in 2023. Spreading field efficiencies improved year over year, from 54% in 2021 to 61% in 2023. For both spraying and spreading operations, of note is the slight decrease in both field and route efficiency in the 2022 season, whereas seeding operations do not reflect this trend. The efficiency decreases observed in 2023 data may be partially attributed to some unexpected software errors encountered throughout the season. Furthermore, it is important to consider the published field efficiency values in the literature. The gray shaded region in figure 2a demonstrates the range and typical values for field efficiency of seeding, spraying, and seeding operations as published in the ASABE machinery data standard D497 (ASABE Standards, 2020a). Lastly, fuel efficiency drastically improved (lower L/ha) for seeding operations between 2021 and 2022 but declined in 2023 because of lower field efficiencies related to smaller field size. Spraying fuel usage declined over the three years. Fuel usage in spreading operations was similar in 2021 and 2023; however, increased considerably in 2022 (fig. 2c). In 2022, the majority of spreading with OP occurred on high rolling terrain farmland, which resulted in higher fuel use than other years, which occurred on flat terrain. The overall improvements align with the technological advancements and upgrades made to OP over the past four years (including a major software change and substantial hydraulically powered transmission upgrades).

Autonomous vs. Conventional Agricultural Equipment

Field and fuel efficiencies of autonomous operations were compared to standard efficiencies of conventional equipment found in scientific literature as well as directly compared to conventional operations completed by the research team in 2022. Literature values were obtained from Canadian and USA publications between 1978 and 2022 (Kepner et al., 1978; Bowers, 1987, 1992; Government of Manitoba, 2022; Hancock et al., 1991; Hanna and Hanna, 2016; Rutherford and Gimby, 1987; White, 1978). While conducting the literature search, only equivalent agricultural equipment was considered for comparison to OP and its implements, such as air seeders or air/grain drills, self-propelled sprayers, and nutrient applicators or spreaders. As shown in figure 3, autonomous equipment performance is in line with conventional data collected and published literature values. OP has a slightly lower field efficiency for spraying and spreading operations compared to both conventional and literature data, however, a higher field efficiency for seeding operations compared to conventional equipment, but lower than scientific literature values. Fuel usage by OP during all operations is slightly higher compared to conventional equipment; however, it is in line with literature data. Overall, both OP and the 2022 conventional equipment performed on par with published literature efficiencies of agricultural equipment.

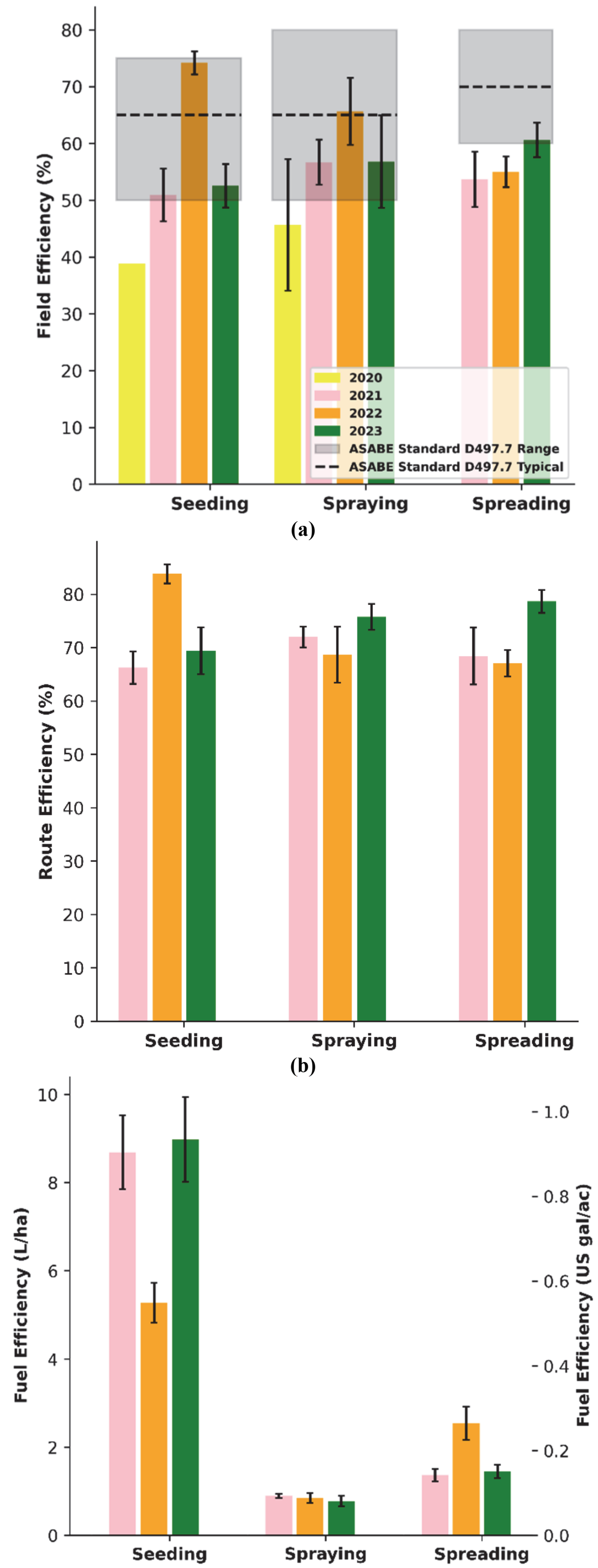

Figure 2. (a) Field efficiency (%) of OP seeding, spraying, and spreading operations in 2020 (where available), 2021, 2022, and 2023 operations. Gray shaded region with dashed line indicates range and typical field efficiency, respectively, from the ASABE D497.7. (b) Route efficiency (%) of OP seeding, spraying, and spreading operations in 2021, 2022, and 2023. (c) Fuel Efficiency (L/ha and US gal/ac) of OP seeding, spraying, and spreading operations in 2021, 2022, and 2023. Error bars represent standard error of the mean (SEM).

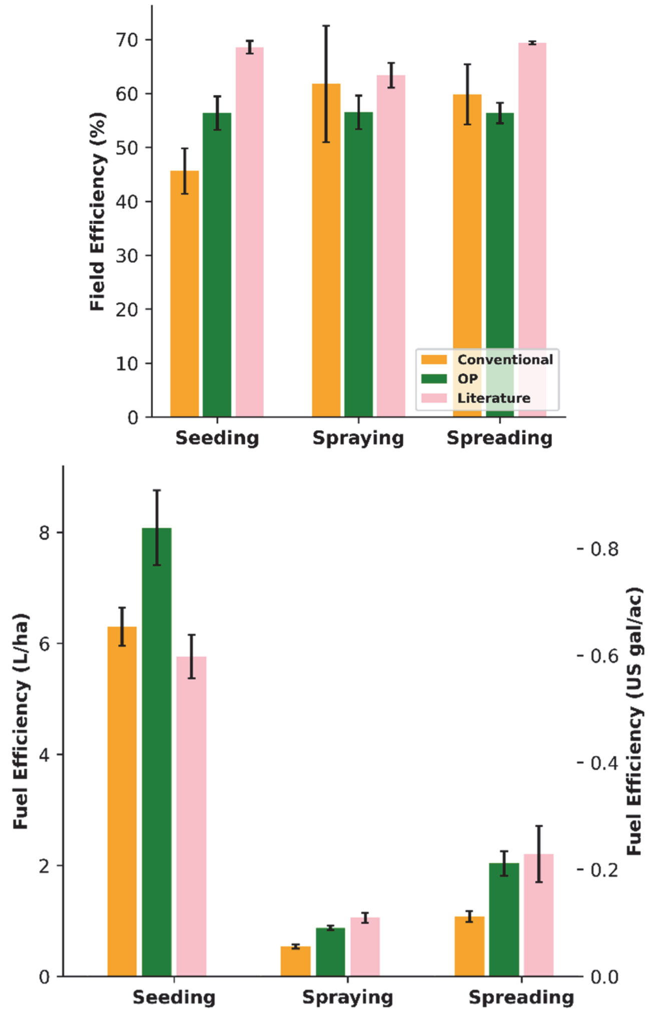

Figure 3. Top: Field efficiency (%) of autonomous (2021–23) and conventional (2022) equipment operations compared to published literature values for seeding, spraying, and spreading operations. Bottom: Fuel usage rate (L/ha and US gal/ac) of autonomous (2021–23) and conventional (2022) equipment operations compared to published literature values for seeding, spraying, and spreading operations. Error bars represent standard error of the mean (SEM).

Further comparison of autonomous to conventional operations in 2022 alone was conducted since field conditions were extremely different between years in central Alberta (a severe heat wave and drought in 2021, versus unseasonably wet and cold in 2022) to eliminate possible influence of ground conditions on the operational data. A summary of the field efficiency, route efficiency, and fuel usage rates of autonomous and conventional equipment during 2022 is shown in table 4, with visual representations in figure 4. It can be seen how autonomous equipment performs analogously to conventional equipment, in some cases exceeding the efficiency of conventional equipment.

Sufficient data were available for formal statistical analysis to determine if autonomous equipment performs significantly differently from conventional equipment during seeding and spreading (but not spraying) operations. One of the most notable findings in these results is how average OP route and field efficiency is greater than average conventional efficiency during seeding operations while using less fuel per hectare (fig. 5). During 2022 seeding operations, OP had a significantly greater average route efficiency than conventional (84% vs. 69%, $p = 0.005$) and a significantly greater average field efficiency of 74% as compared to the conventional seeding equipment average field efficiency of 46% ($p = 0.0003$). Although the average fuel usage rate (5.28 L/ha) of OP was lower than that for conventional equipment (6.3 L/ha), this difference was not statistically significant ($p = 0.097$).

Another notable finding is how OP average route and field efficiency (67% and 55%, respectively) is lower (although not significantly: $p = 0.4, 0.4$) than average conventional route and field efficiency (72% and 60%) during spreading operations (fig. 6). OP used significantly more fuel on average (2.5 L/ha) during spreading operations as compared to average conventional equipment (1.1 L/ha) fuel usage ($p = 0.00002$). Differences between fuel usage can be attributed to field terrain. The majority of spreading with OP occurred on high rolling terrain farmland, which will result in higher fuel use when compared to the conventional equipment, which operated on relatively flat land.

Case Studies

There may be differences in efficiencies of equipment working on the same fields, due to equipment differences, human judgment, and field conditions. For example, one field was sprayed by autonomous equipment in 2021, and the same field was sprayed conventionally in 2022 (both machines had the same working widths, table 2); OP's algorithm and field mapping software suggested spraying AB lines in an east-west direction, versus an operator who sprayed the same field in the north-south direction (fig. 7). This difference in judgment contributed to a lower field efficiency of the conventional sprayer compared to the autonomous operation; OP field efficiency of 74.2%, versus conventional sprayer field efficiency of 51% (table 5). Moreover, the conventional sprayer was able to complete the job faster, but it also traveled a greater distance than OP. Idle time/travel of the conventional sprayer more negatively influences its field efficiency because its TFC is much higher than the OP's due to its higher rated ground speed. Route efficiency was nearly equal for both pieces of equipment. The conventional path has a longer distance, more overlaps, and longer AB lines. Although the conventional sprayer spent less overall time in the field than the autonomous

Table 4. Average efficiency parameters measured for autonomous and conventional operations during the 2022 field season (April 2022 – October 2022).

	Field Efficiency (%)		Route Efficiency (%)		Fuel Efficiency (L/ha)	
Operation	Autonomous	Conventional	Autonomous	Conventional	Autonomous	Conventional
Seeding	74.2	45.6	83.8	69.3	5.3	6.3
Spraying	65.6	61.8	68.7	77	0.8	0.5
Spreading	55	59.8	67.0	72.4	2.5	1.1

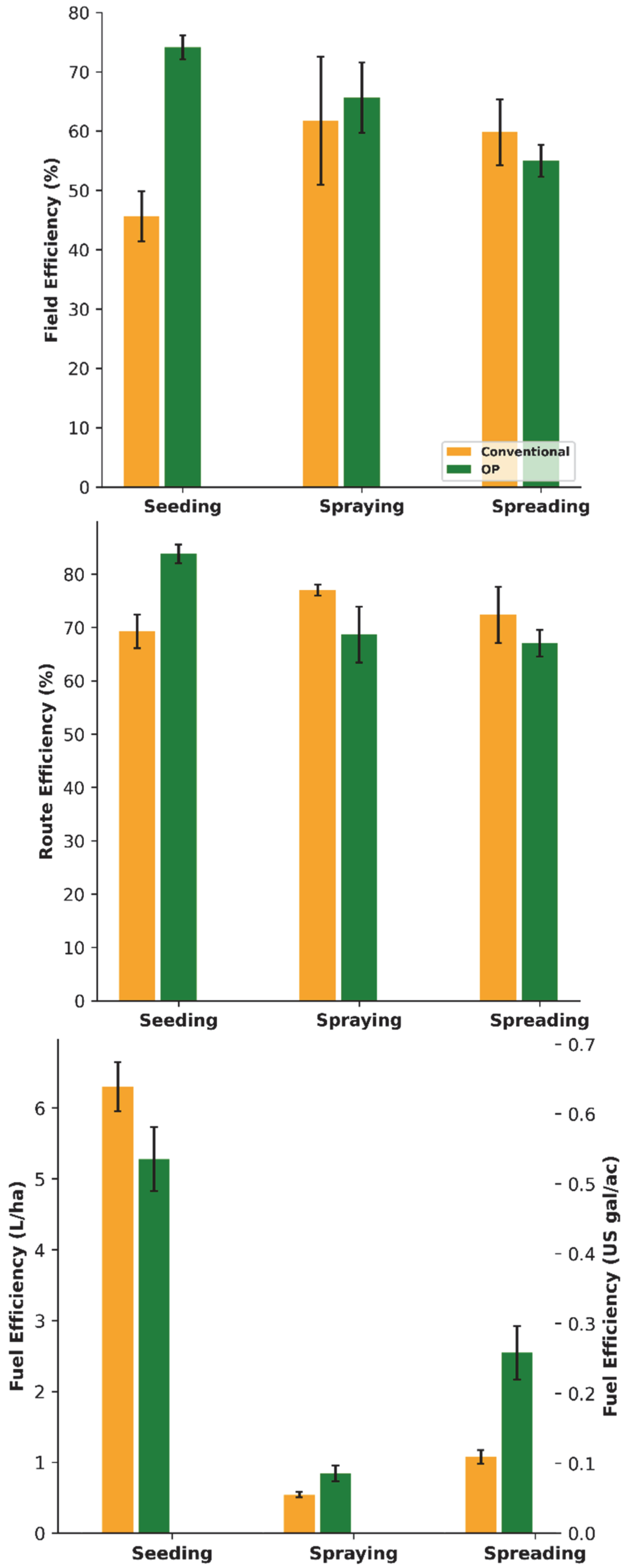

Figure 4. Top: Field efficiency (%) of autonomous and conventional equipment operations in 2022 for seeding, spraying, and spreading operations. Middle: Route efficiency (%) of autonomous and conventional equipment operations in 2022 for seeding, spraying, and spreading operations. Bottom: Fuel usage rate (L/ha and US gal/ac) of autonomous and conventional equipment operations in 2022 for seeding, spraying, and spreading operations. Error bars represent standard error of the mean (SEM); for fuel efficiency, they are in L/ha units.

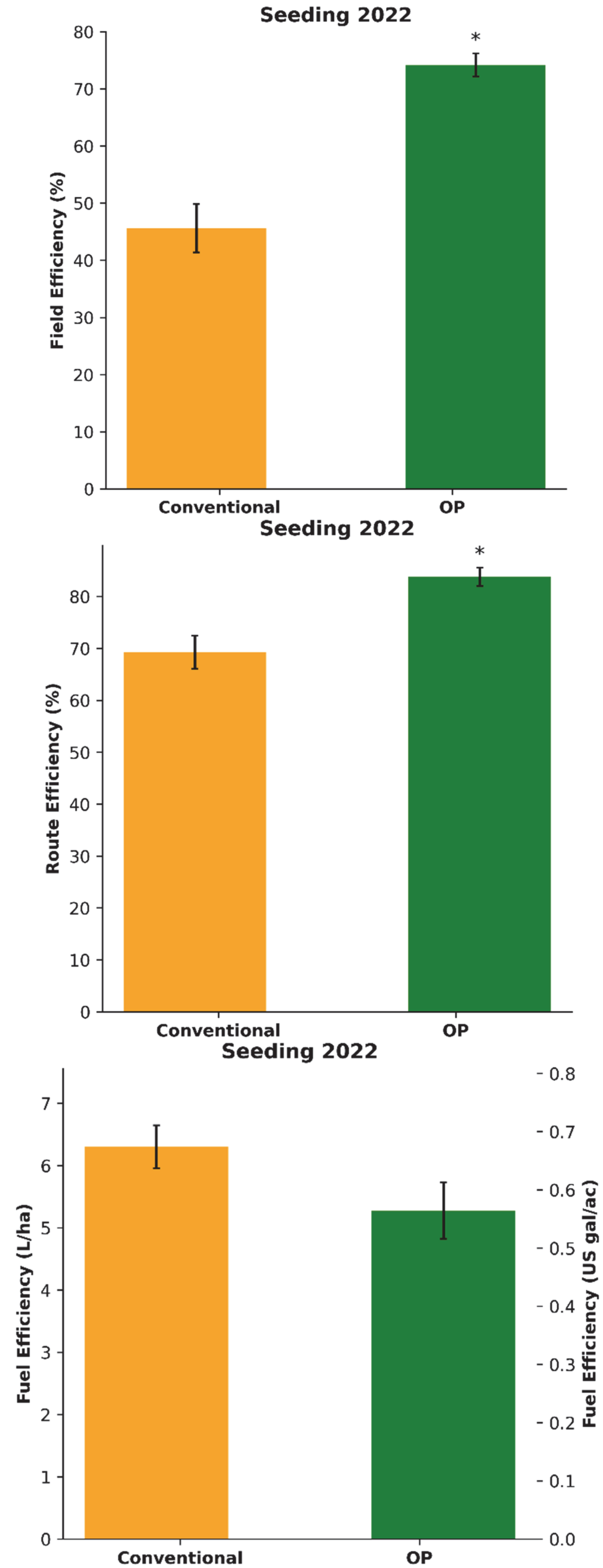

Figure 5. Field, route, and fuel efficiency of autonomous and conventional equipment operations in 2022 for seeding operations. Error bars represent standard error of the mean (SEM). Asterisk indicates statistically significant differences between groups.

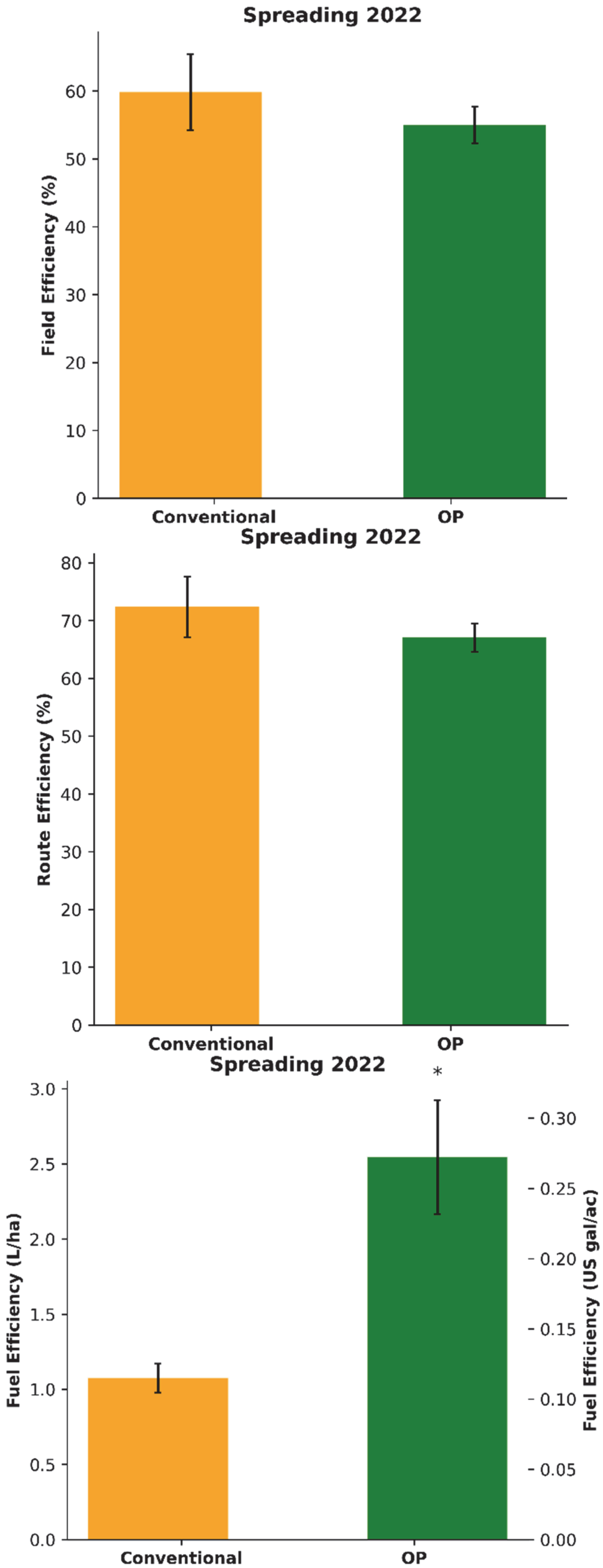

Figure 6. Field, route, and fuel usage rate of autonomous and conventional equipment operations in 2022 for spreading operations. Error bars represent standard error of the mean (SEM). Asterisk indicates statistically significant differences between groups.

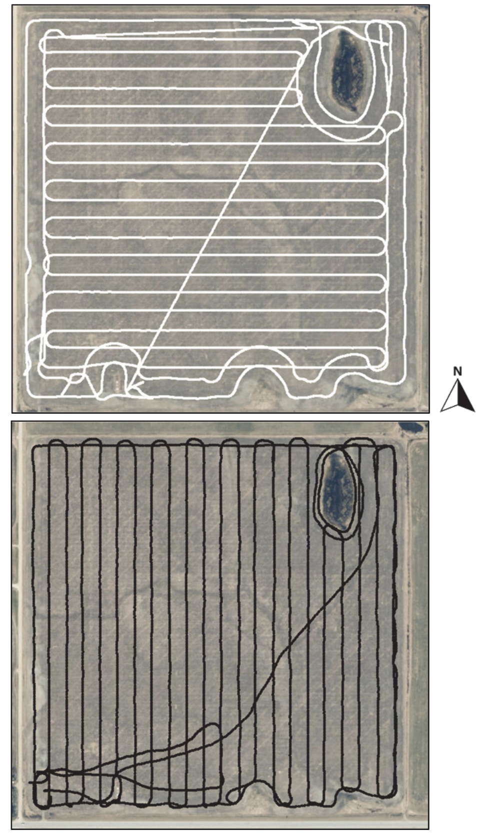

Figure 7. The top image shows an autonomous spraying operation in 2021; the bottom image shows the same field sprayed by a conventional self-propelled sprayer in 2022.

Table 5. Comparisons between autonomous and conventional spraying equipment for the same field in 2021/2022.

Metric	OP	Conventional
In field time (hours)	2.33	1.76
Total distance traveled (km)	21.56	22.53
Average working speed (km/h)	9.51	19.5
Field Efficiency (%)	74.22	50.96
Route Efficiency (%)	76	78

operation lasted (approximately 30–45 mins less), it has a lower field efficiency due to its higher average working speed; therefore, its theoretical field capacity is much higher than that of OP.

Another example of a direct field comparison study is with the use of a nutrient applicator (spreader). One field was spread conventionally in 2022 and repeated with OP in 2023 using the same application rate and swath width. Both operations were completed without reloading inputs. Route mapping shown in figure 8 illustrates differences between OP and conventional routing specifically at headlands and around obstacles (fig. 8), which results in a lower autonomous performance (table 6). In this case, the conventional unit created a more efficient route plan (28 km traveled) than the OP-generated route plan (33.3 km traveled), resulting in lower field and route efficiencies. Autonomous routing is dependent on constraints governed by the equipment used, such as turning radius and obstacle buffer zones. These differences in constraints between routing methods and equipment types can greatly affect efficiency outcomes.

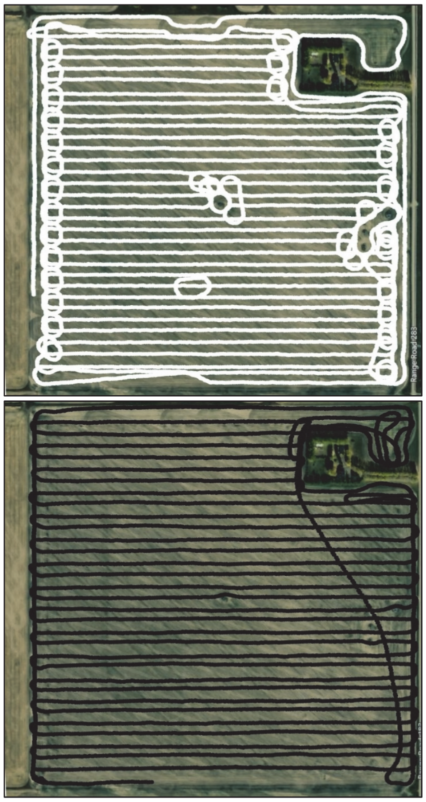

Figure 8. Top image shows autonomous spreading operation in 2023; bottom image shows a conventional self-propelled spreader operation in 2022.

Table 6. Comparisons between autonomous and conventional spreading equipment for the same field in 2022/2023.

Metric	OP	Conventional
In field time (hours)	2.68	1.2
Total distance traveled (km)	33.29	28
Average working speed (km/h)	12.41	24.06
Field Efficiency (%)	77.99	90.15
Route Efficiency (%)	78.02	90.94

In May 2022, a synchronous seeding operation was performed where autonomous and conventional seeding equipment worked in the same field at the same time, sharing the same as-applied map and communicating with one another electronically. OP completed the headlands, while a conventional seeder worked AB lines (fig. 9). Autonomous operation accomplished 17.3 ha of the total 59.13 ha, approximately 30% of the seeding area. OP with its compact seeder implement (9.1 m) was very beneficial for this task, as the very wide conventional seeder implement (18.3 m) would have been much less efficient completing headlands, since many turns and irregular driving patterns were required.

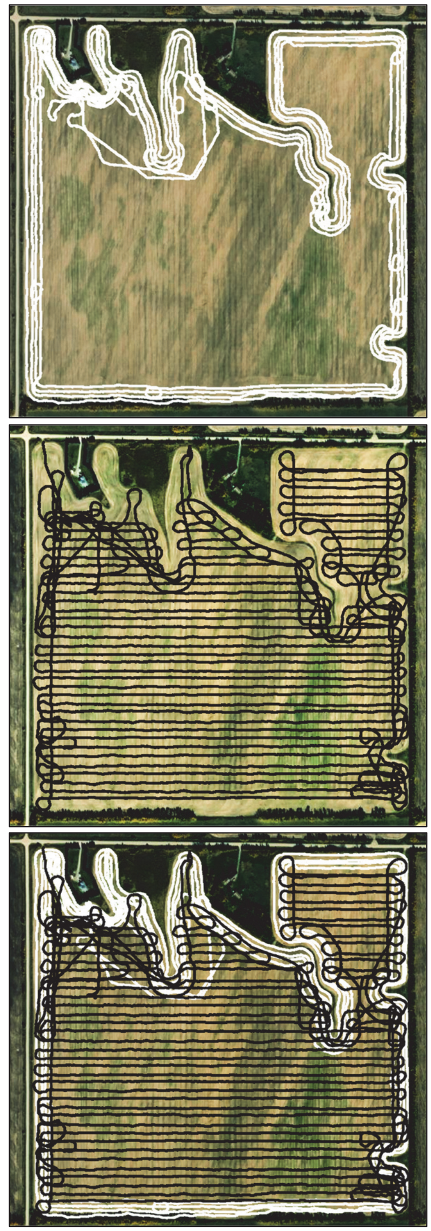

Figure 9. Synchronous seeding operation in central Alberta on May 23, 2022. Top image shows the white path of OP seeding the headlands, the middle image shows the path of a 2020 Case IH Steiger 420 with 2019 Seed Master Ultra SR seeding AB lines, and the bottom image shows the paths of both pieces of equipment as they worked simultaneously.

Discussion

As OP was the only viable autonomous platform available for broad acre production during the time of study, limitations were evident. Direct equipment comparisons were difficult to arrange (e.g., autonomous versus conventional operation in the same field in the same year). The OP seeder was smaller in width compared to present-day conventional sizes; sprayers and nutrient applicators shared similar widths and capacities; however, OP lagged in engine power in comparison, and other implements such as vertical tillers and harvesting equipment were not available or compatible with the OP platform. Direct field comparisons were also challenging due to differences in field conditions and climate change from year to year. Barring these limitations, a robust data set was collected which enabled insight into the relationship between field and route efficiencies and field size described in detail later. Given the types of limitations and constraints associated with this research, it is important to realize that the case studies and comparisons with literature values presented are not intended to be definitive, conclusive comparisons and are presented as observational results.

Field and Route Efficiencies and Field Size

OP was intentionally designed as a small seeding machine, created in response to increasingly larger equipment being continually produced; hence why the OP-compatible seeder implement is considerably narrower (9.1 m / 30 ft) than typical seeding equipment used in the Canadian Prairies (12.2 m / 40 ft to 30.5 m / 100 ft). As the OP design progressed, the sprayer and spreader implements were designed larger than the seeder while maintaining a much lower engine power capacity of 129 kW. With the exception of the seeder implement, OP has similar implement widths, tank volumes, and total weight as comparable conventional equipment used in 2022 (table 2). The relationship of field size to field efficiency differs between OP and conventional equipment, and this difference can be attributed to equipment size in the case of seeding, but for spraying and spreading, the difference is likely due to other factors. It has been reported that implements with wider working widths actually have lower field and fuel efficiencies compared to narrower implements, although wider equipment operating at the same speed as a smaller unit is able to accomplish more area per hour (Grisso et al., 2002; Hanna and Hanna, 2016). A wider piece of equipment requires much more space and time to turn and accomplish headlands and often results in a larger headland area than a smaller unit (Hanna and Hanna, 2016). In the case of the OP spreader and sprayer, reasons why it performs with greater efficiency than conventional equipment may be due to its larger tank size but same working width, therefore less time spent in the field for filling and maintenance to cover the same area. The results shown in figure 10 demonstrate a trend that supports the scientific literature; OP achieved greater field efficiency than conventional equipment on similar sized field areas. A comparable trend is seen for route efficiency, where OP has a greater efficiency than conventional equipment on similarly sized fields, although the difference is less between them as compared to field efficiency (fig. 10). The 2023 decrease in seeding field efficiency can be reasoned due to the increased frequency of small field sizes seeded in 2023, which tend to yield lower field efficiencies (fig. 10).

CONCLUSIONS

The results of this paper demonstrate how autonomous equipment may be a beneficial agricultural asset for a producer and that specifically OP efficiency and fuel usage have improved over the past few years to a point that it rivals typical equipment used on farms in the Canadian Prairies. For seeding, OP outperformed conventional equipment in terms of efficiency and fuel usage. For spraying and spreading tasks, OP performs on par with conventional equipment measured performance and literature review findings. Two case studies were performed with both conventional and OP equipment on the same field, one spraying operation and one spreading operation. Both studies also indicated OP performs on par with conventional equipment but did discover constraints with the OP technology as well, which, when addressed, improve performance.

OP has several advantages in terms of economic and environmental benefits. Firstly, as an example, the seeder has a smaller physical footprint; therefore, it causes less compaction to soil and less damage to crops. OP carries its implement using only four wheels that compact soil as compared to conventional seeding equipment requiring a tractor unit towing the seeding implement with multiple wheel combinations and higher overall weight contributing to increased wheel tracks/compaction. Secondly, as shown in this paper, OP has greater route efficiency, driving as little as possible to accomplish the task required, part of the route optimization within the autonomous route planning software. OP has a high field efficiency, especially in smaller fields, making it a feasible option also in irregularly shaped fields where headland contours are a major portion of the travel pattern. Autonomous operation has the advantage over conventional methods by its ability to provide recurring efficient routing in areas such as headland turns, which is not influenced by human intervention, which sometimes can decrease efficiencies. The future direction that this project may take is to establish how autonomous equipment performs in larger-sized fields (>160 ha) compared to conventional equipment, which has been increasing in size in response to larger agricultural area coverage demands. This leads to potential research on the swarm capabilities of autonomous agricultural equipment as well as larger operational areas. At this time, our findings point in the direction that supervised autonomous solutions on the farm can support producers by saving them time and resources, reducing excessive environmental degradation, and accomplishing tasks to the same caliber as current typical methods. Research in this domain is essential to further develop autonomous capabilities in the strive for fully autonomous machinery and the confidence to utilize this type of technology in the agricultural industry.

SUPPLEMENTAL MATERIAL

The supplemental materials mentioned in this article are available for download from the ASABE Figshare repository at: https://doi.org/10.13031/28339904

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CONFLICT OF INTEREST

Travis A. Burgers is an employee of CNH Industrial (formerly Raven Industries). Raven Industries funded this study and provided in-kind technical support. Travis A. Burgers has patents (granted or pending) for which Raven Industries is the assignee but none related to the OMNiPOWER platform.

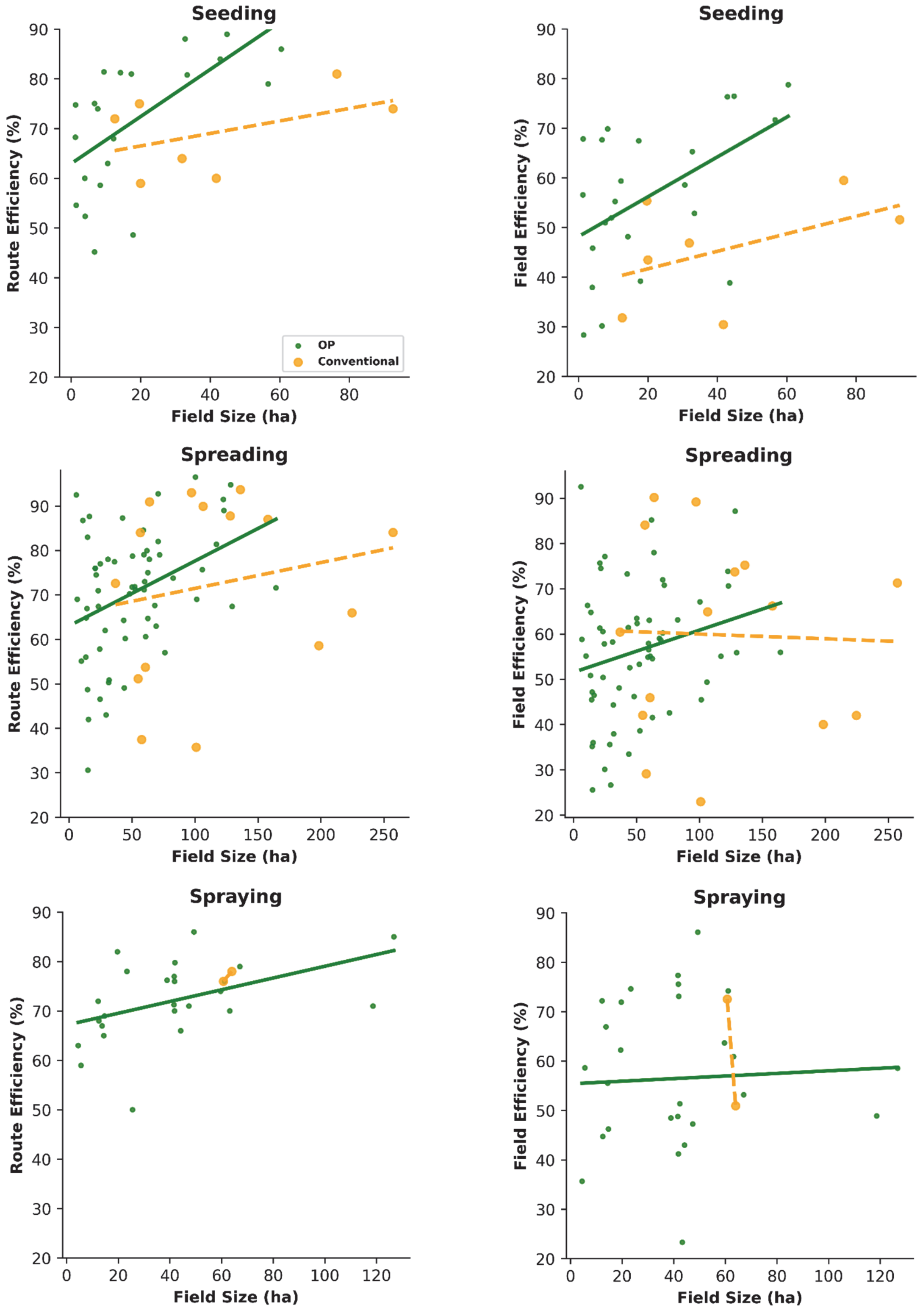

Figure 10. Scatter plots showing relationship between field efficiencies, route efficiencies (%), and field size (ha) for autonomous (2021–23) and conventional (2022) operations by operation type. Solid and dashed lines show linear fit.

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NOMENCLATURE

BMPs = Best management practices

CAN = Controller Area Network

EFC = Effective field capacity

OCSF = Olds College Smart Farm

OP = OMNiPOWER, autonomous system from Raven Industries

PA = Precision Agriculture

SEM = Standard error of the mean

TFC = Theoretical field capacity